The Use of Sensor Derived Data in Optimization along the Mine-Value-Chain

An Overview and Assessment of Techno-Economic Significance

Mike Buxton, Jörg Benndorf – TU Delft, the Netherlands

Abstract

Sensor derived data can add value across the mining operating chain ranging from resource definition, extraction, pre-concentration, mineral process monitoring and assessment of product quality.

Most documented studies on sensors in mining focus on specific technologies for specific applications. These studies do not take into account different aims, objectives and operating conditions at different steps in the value chain.

The first part of this contribution assesses key physical performance and discriminatory requirements of sensors applied in each portion of the mining value chain. The second part proposes a framework of methods for quantifying the value added by additional sensor information. Integrating the sensor based technology and the economic value quantification allows for both, designing an economically optimal sensor monitoring network along the whole mining value chain and optimizing efficiencies.

Illustrative studies demonstrate the significant economic benefits, in particular in reduction of exploration expenditures, increase in extraction efficiencies, increase in ore product quality and improvement of processing efficiencies.

Key words

Sensor based material discrimination, real time optimization

Introduction

Sensor derived data can add value across the mining operating chain ranging from resource definition, extraction, pre-concentration, mineral process monitoring and assessment of product quality. Historically sensors have usually been viewed in terms of pre-concentration [1] or on-line characterisation [2].

Documented studies often refer to specific sensor technologies such as Near Infra Red [3], Dual Energy X-Ray Transmission [4], electromagnetic [5] or optical [6]. Applications are qualitatively described. Economic benefits are seldom documented. The purpose of this contribution is to define an illustrative framework for the application of sensors across the mine production cycle and explicitly describe potential economic benefits. It is hoped that the ability to illustrate and quantify potential economic benefit will stimulate further research and development in this promising application field. It should be noted that all costs and potential revenues are high order indicative estimates and should not be considered definitive.
Figure 1: Potential locations of sensors for material characterization in exploration, extraction and processing of raw materials.

Figure 1 illustrates the proposed use of sensors in a typical mine production cycle. Applications considered here include resource definition, mine planning and grade control, extraction monitoring, pre-concentration and product quality assessment. The sensor data derived at each step can be used for real-time decision support for process optimization. The contribution is divided into two parts. Part one assesses high order requirements for sensor technologies at each process stage. Part two demonstrates the potential added value by the means of illustrative examples.

**Sensors in Mineral Industry**

It should be noted that at present existing sensors are incapable of fulfilling the requirements and applications described. However, this overview will identify gaps and specific conditions that need to be addressed in the future to harness the full economic opportunities.

**Resource Definition**

The process of resource definition is currently achieved by drilling and physical sampling ahead of mine development. Additional data are acquired from blast holes. The purpose of such drilling and sampling is to determine grade, continuity, percentage ore & waste and geometry of the ore body.

Replacement of this process by means of sensor acquired data has to cover all the requirements from physical analysis and measurement of actual rock material at adequately very high analytical resolution, precision and repeatability. As a result, sensor requirements include an ability to discriminate grade based either on direct detection
and measurement or by measurement of a calibrated proxy. Sensors need to detect ore & waste mineralogy together with texture. From this density, hardness and mineral liberation potential can also be statistically inferred. Sensor data need to be acquired directly from the drill samples without the necessity for pre-preparation or alternatively can be acquired in-situ down-hole. The down-hole application may eliminate the necessity for physical retrieval of drill core. The time requirement for analysis and interpretation of the data are in the order of minutes or hours. A sensor combination can eliminate the necessity for sampling and analysis in an offline laboratory thereby saving time and the cost of chemical analysis.

**Mine Planning and Grade Control**

Grade control requires the discrimination and monitoring of previously defined domains or zones characterized by uniform properties such as grade, mineralogy and physical properties. The purpose is to define mineable units and monitor the physical process of extraction to ensure compliance with the schedule plan. The sensor requirement here is to measure a limited suite of parameters directly applicable to grade control. Sensor requirements are therefore to measure parameters at the working face that correspond with specific grades and material types. This can be measured in a static fashion. Ideally the data should be in image format and spatially constrained. Measurements can include direct measurement of mineralogy or measurement of clearly defined proxies based on prior calibration. Data acquisition and interpretation should be “live” or real time in order to directly influence mining.

**Pre-sorting or Pre-upgrading**

Post mining and pre-crushing there is considerable scope to eliminate waste or deleterious material.

The sensor data can control dispatch decisions and as a result control allocation of material to specific destinations such as waste dump, feed stock-piles or direct feed. The function is to reduce high initial material variability to generate a more homogeneous product. The information can ensure correct decision making for material allocation.

Sensor requirements include the ability to discriminate grade, chemistry and/or mineralogy in real-time. The measurement has to be in a dynamic environment on a moving flow of material. The time constraint is onerous, since there will be a continuous high volume flow of material in the order of magnitude of 5kt/h to 10kt/h peak. A sensor system has to be able to accurately measure specific parameters defined from previous calibration, the support system has to be able to analyze the sensor data and define decisions in real time. Particle by particle measurement and discrimination would be preferred however due to huge quantities of material per unit time the technical feasibility is questionable. An alternative is to measure the material stream continuously and analyze on the basis of a moving average. The ratio between moving average window and hourly production needs to be defined to achieve the correct level of precision for a significant portion of the material stream. Significant portion in this
sense describes the minimum increment that can influence process efficiency and recovery. For example in a production of 5kt/h a measurement every 100t increment or approximately a minute would be sufficient to ensure control of specified qualities at a statistically significant level.

**Post-stockpile and pre-concentration**

Key differences from a “post mining and pre-upgrading” scenario and a “post-stockpile—pre-concentration” scenario are reduced variability, and pre-defined and pre-constrained quality specification coupled with a more continuous flow of material. The requirement is to remove residual variability prior to processing and to provide information to control processing parameters. The requirement is to measure a controlled material stream that has already been defined. Sensor requirements therefore are direct measurement of characteristics that define the desired product qualities. This is likely to include assessment of mineralogy but may also include physical properties. The material volume to be measured is less than in the previous stage, but measurements need to be made in a dynamic real-time framework. Analytical precision and repeatability need to be high.

**Post-Processing and quality control**

Sensor based material characterization in this application is to ensure adherence to product quality specifications and to provide reconciliation data for real time process monitoring and control.

The material to be analyzed will display relatively small variability. The requirement is for representative high-precision sub-sampling of the product stream and to eliminate the necessity for off-line analysis. Analysis has to be completed real-time. Table 1 provides a qualitative summary of sensor requirements and operating conditions at various stages of the mine production cycle.

<table>
<thead>
<tr>
<th>Process stage</th>
<th>Variability of measured material</th>
<th>Volume to be measured</th>
<th>Required analytical precision</th>
<th>Time available for measurement and interpretation</th>
<th>Working environment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Resource definition</td>
<td>Very high</td>
<td>Small</td>
<td>Very high</td>
<td>Static, Minutes to hours</td>
<td>In-situ-down hole or drill chips/core</td>
</tr>
<tr>
<td>Mine planning and grade control</td>
<td>Very high</td>
<td>Small to medium (work face)</td>
<td>Medium</td>
<td>Static, Minutes to hours</td>
<td>Operational mine environment</td>
</tr>
<tr>
<td>Pre-sorting or Pre-upgrading</td>
<td>High</td>
<td>Very high</td>
<td>Medium</td>
<td>Dynamic, real-time</td>
<td>Operational mine environment</td>
</tr>
</tbody>
</table>
Table 1: Sensor requirements and operating conditions at various stages of the mine production cycle.

### Quantification of Value Added

To evaluate the potential economic impact of sensor applications along the chain of mining the next section presents concepts of application and illustrative examples. The aim here is to illustrate opportunities for both decreasing costs and increasing revenue along the exploration, mining and beneficiation process of raw materials and to estimate a first order magnitude of financial impact. Chosen examples reflect the previously discussed stages of exploration, mine planning and grade control, post-extraction and pre-concentration. Costs were derived from public domain sources, in particular InfoMine [7].

### Sensors in exploration

The case is to eliminate the current practise of physical sampling and analysis of samples in an off-line laboratory. Three examples are chosen to represent typical exploration practices and implied expenditures for copper, iron ore and coal. An illustrative cost of $15 per sample has been assumed including sample preparation and assay analysis but excluding sample collection and dispatch.

Resource definition in a typical large copper porphyry mine requires in total over life of mine approximately 3,500+ boreholes, 500,000m+ total drilling and 40,000+ individual samples. Considering $15 per sample indicative cost reduction for sample analysis is in the order of $600,000. A drilling at a rate of 250 holes per year comprising 40,000m yielding 2,500 samples indicates a cost reduction of $37,500 per year.

A typical BIF Iron Ore mine requires 120,000 boreholes comprising 1,500 km drilling and acquisition of 220,000 individual samples. This suggests a an analytical cost of $3,300,000. Potential cost reduction due to sensor derived data are in the order of $100,000 per annum.

Mining a typical tabular coal deposit at 10 mio. t/a open cast with an average seam thickness of 10m and using a resource delineation drill hole spacing of 80m requires 1,400m of coring per year. Replacing off-line quality analysis of core samples by real-time on-line or in-situ sensor data saves approximately $21,000 per annum in analytical costs.
Additional savings will be realized by reduction in time required since physical sample collection and submission to a laboratory can be eliminated. In addition the sensor derived data can be immediately available for use in decision making.

**Short-term mine planning and grade control**

A typical application of sensor-based material characterization includes face-mapping. Based on static sensor derived maps of the current digging face and statistical inference methods linking the sensor responses to actual physical rock properties, mineral types and grades the level of confidence in the prediction of in-situ material characteristics is expected to improve significantly. The gained knowledge has impact on short-term production scheduling, in particular on actual sequencing, block delineation, and dispatch decisions. Cost reductions are expected through increased plan compliance by decreasing the amount of reactive decisions and increasing the time the operation acts according to plan. Unscheduled down-times due to re-location of production equipment because of grade control constraints will decrease.

A major reduction in costs and increase in revenue is expected by improving dispatch decisions. Increasing the knowledge about material characteristics will decrease the frequency of miss-classification and misallocation of material. The example below illustrates the method of evaluation using loss functions and quantifies the financial implication on an illustrative case.

The occurrence of prediction errors of block grades leads to four cases classifying in-situ blocks and allocation of material to defined destinations. These four cases are
- Case I: In-situ ore is correctly classified as ore and allocated accordingly.
- Case II: In-situ ore is incorrectly classified as waste and allocated wrongly.
- Case III: In-situ waste is incorrectly classified as ore and allocated wrongly.
- Case IV: In-situ waste is correctly classified as waste and allocated accordingly.

![Figure 2: Classification of mining blocks based on prior information to mining.](image)
Economic quantification uses a so called loss-model [e.g. 8, 9].

\[ L_M = p_p - p_a \]

The loss due to misclassification \( L_M \) is the difference between potential profit assuming perfect classification \( p_p \) and actual profit based on the actual dispatch decision \( p_a \). For Case II a simple estimation is given by

\[ L_M_{\text{Ore/Waste}} = p_{\text{Ore}} - p_{\text{Waste}} = \left( e_{\text{Ore}} - c_{\text{Process Ore}} \right) \cdot t \]

where \( L_M_{\text{Ore/Waste}} \) represents the loss due to ore blocks send to the waste dump, \( e_{\text{Ore}} \) are potential earnings selling the product after processing a ton of ore, \( c_{\text{Process Ore}} \) are costs of processing a ton of ore and \( t \) is the tons per mining block.

Misclassification of the type shown in Case III results in the following loss

\[ L_M_{\text{Waste/Ore}} = p_{\text{Ore}} - p_{\text{Waste}} = \left( c_{\text{Penalty Waste}} \cdot \Delta_{\text{Grade}} \right) + c_{\text{Process Ore}} - e_{\text{Ore}} \cdot t \]

where \( L_M_{\text{Waste/Ore}} \) represents the loss due to waste blocks send to the processing plant, \( e_{\text{Ore}} \) are potential earnings selling the product after processing a ton of ore, \( c_{\text{Process Ore}} \) are costs of processing a ton of ore, \( c_{\text{Penalty Waste}} \) are costs associated with sending material out of specification to the processing plant. These costs are a function of the grade and include the decrease in process performance and a reduced quality of the final product. \( t \) is the tons per mining block.

To estimate an order of magnitude in an illustrative example in a typical Channel Iron Ore deposit the following can be assumed:

- Ore is mined using block sizes of 25 by 25m with bench high of 10m representing 6,250 m³. Assuming a density of the ore of 3.0 t/BCM a block contains of approximately 18,750t.
- Depending on commodity, operation and contractual setting \( L_M_{\text{Waste/ore}} \) and \( L_M_{\text{Ore/Waste}} \) may have a magnitude between $1 to $100 per ton. Assuming a loss of $10 per ton misclassifying one block results in a loss in the order of $180,750.
- For estimation of the actual amount of misclassification Abzalov et al. [10] provides a reference for a typical iron ore operation in Western Australia. The misclassification is estimated at 5% for a drill-hole spacing of 5m × 5m and 12% for a drill hole spacing of 25m by 25m.

With an annual production of 15 mio. t represented by approximately 1,000 mining blocks that implies 50 to 120 blocks are misclassified. This corresponds to a potential loss of $7,500,000 to $18,000,000. An increase in the precision of estimating grades by incorporating sensor derived data from face mapping demonstrates a huge benefit. A decrease in misclassification by only 10% indicates a potential increase in revenue of $750,000 to $1,800,000 per year.
**Sorting after extraction**

Sensor-based material characterisation after extraction can be implemented after in-pit crushing or on a conveyor prior to stockpile or direct feed. Three potential benefits can be identified described in the next three sub-sections.

**Case 1: Decrease of misclassification**

Decrease in misclassifying blocks and incorrect allocation. Note that the decision of dispatching is transferred from pre-extraction, mine-planning and grade control, to post extraction.

**Case 2: Increased efficiency in extraction due to decreased requirements in selectivity**

Portions of the block representing dilution can be sorted out and dispatched separately. Decoupling selective mining from grade recovery bypasses the volume-variance-relationship and maximizes equipment efficiency while maintaining recovery traditionally achieved through selective mining. For example Figure 3 shows illustrative grade-tonnage-curves for a push back in a Cu deposit dependent on a mining block size. Considering a cut-off grade of 1.0% an SMU of 5m × 5m × 5m yields 1.250kt of ore, a SMU of 25m × 25m × 10m would only yield 1.000kt.

![Figure 3: Grade-tonnage relationship as function of cut-off grade.](image)

Utilizing sensor based sorting of excavated material, the dilution introduced by larger block sizes can be eliminated. Blocks, which are in-situ under cut-off grade can
be upgraded after extraction to meet economic requirements. The effect is an increase in usable material comparable to utilizing smaller block sizes by eliminating the constraints imposed by selectivity.

As documented in various references [11] larger block sizes lead to improved overall economics as unit costs for drilling, blasting, extraction and hauling decrease. As shown in Figure 4, Hekmat et al., [11] illustrated a reduction in costs and corresponding increase in life of mine of 5%. Assuming production costs of $5 per ton and an annual production of 15 mio. t the economic benefit can be quantified as approximately $3,750,000 per year.

Figure 4: Economic life of the mine as function of block dimensions (after 11).

**Case 3: Eliminating zero-value material from material handling in an early process stage**

Eliminating zero-value material out of the process in an early stage will decrease overall transport and handling costs. In addition, subsequent elements in the logistic chain, such as, central conveyors or shafts can be either downsized to accommodate smaller volume or utilized to maximum capacity by only handling value generating material.

An illustrative example is given by an underground coal operation. Mining is hampered by the presence of micro faults with displacements of a few meters (Figure 5). These cannot be adequately be delineated by exploration and as a results cannot be incorporated into panel layout [12].

The presence of faults introduces waste material into the logistic chain. Assuming displacements of 2m and the limited ability of long wall equipment to follow strongly varying geology this can easily result in up to 5% of waste material being incorporated in material handling. The ability to eliminate this waste immediately after extraction and place it directly into a waste dump or use it as back-fill will allow utilization of the
full capacity of the ore hoisting system for value adding material while decreasing costs due to not hoisting zero value material. Assuming a 5 mio. t annual production, 250kt of waste can be eliminated from the hoisting process. With a hoisting cost of $1 per ton a saving of $250,000 can be realized considering only the shaft and excluding any other material handling cost.

**Post-stockpile and pre-concentration**

Sensor based sorting applications between feed-stock-pile and processing plant have a high potential to increase process performance by eliminating remaining zero- to low-value material from the process thereby increasing the quality of feed material. For two typical examples the economic impact is assessed.

The first case investigates a copper concentrator where the amount of concentrate produced is mainly a function of the grade of ore feed. The example considers a typical copper concentrator with an annual production of 600,000t concentrate. The feed grade of copper is assumed to be on average 1%. Dilution during the mining process introduces 5% waste material into the ore extracted. Taking the dilution into account, effectively an average ore grade of 0.95% is processed. Using a simple assumption of linear increase in concentrator recovery as function of grade, eliminating the 5% waste will increase the production of concentrate by 5% as well. The annual production has the potential to increase by 30,000t of copper concentrate. The substantial economic benefit becomes obvious when applying an average revenue for copper concentrate of $1,500 per ton, which results in a potential annual increase in revenue of $45,000,000.

The second case investigates commodities where quality requirements in terms of upper and lower limits of certain elements define processing efficiency. A typical example is iron ore and steel making. Figure 6 shows in-situ iron ore from a Channel Iron Ore deposit in Western Australia. Scattered occurrence of clay pollute the ore as they
introduce alumina. Due to the small dimensions of the clay occurrences, they cannot be eliminated by means of selective mining.

Figure 6: Picture of clay (shown in lighter coloration) occurrences in a Channel Iron Ore Deposit, Western Australia.

As shown in Figure 7, Benndorf and Dimitrakopoulos [13] showed that even sophisticated long- and short-term mine planning methods are not able to solve the challenge of meeting the requirements for alumina for this specific deposit. As a result the ore has to be blended in order to upgrade it for use in steel making.

Figure 7: Uncertainty in meeting production targets for alumina.

The ability to eliminate the pollutants in the ore by using sensor based sorting technologies opens up a completely new set of opportunities for this type of deposit. These opportunities include increased efficiencies in equipment and mine design, material handling systems, production scheduling, opportunities for direct sale of ore without the necessity of blending and opportunities to enter new markets and acquire new customers due to higher ore qualities. A quantification of economic impact including all opportunities is difficult. The Authors expect the order of magnitude to be multiples of tens of millions of $ per year.
Conclusions and Recommendations

This contribution has demonstrated that sensors have the potential to reduce variability along the mining production cycle allowing for increased predictability of subsequent process steps, allowing quantification of uncertainty and improvement of system- and process control. The use of sensors should aim to eliminate zero-value material as early as possible from the production process. The full benefits are realized by integration into a real-time process monitoring and control framework.

Figure 8 summarizes the order of magnitude of potential economic benefits of using sensor derived data in the different stages of the mine production cycle for average sized mining operations. It can be seen that there is a substantial incentive for the application of sensors in all stages. In particular the application of sensors at the extraction and pre-concentration stages would yield immediate pay-back and provide the opportunity for significant business improvement.

![Figure 8: Summary of potential annual added value utilizing sensor based material characterization for average sized mining operations.](image)

The indicative economic benefits suggest that an investment in sensor technology research and development together with specific application definition can be justified in an unarguable business case.

To realize the full potential of sensor technologies for discrimination, material characterization and sorting it will be necessary to develop new approaches in

- Mine design incorporating the ability of sorting,
- Definition of SMU and accompanying impacts on recovery and equipment selection,
- Data analysis and real-time feed back into resource/reserve model and
- Real-Time optimization of decision making at the different stages.
References


